Additive Bayesian Network Modeling – alternative to multivariable regression?

Outline

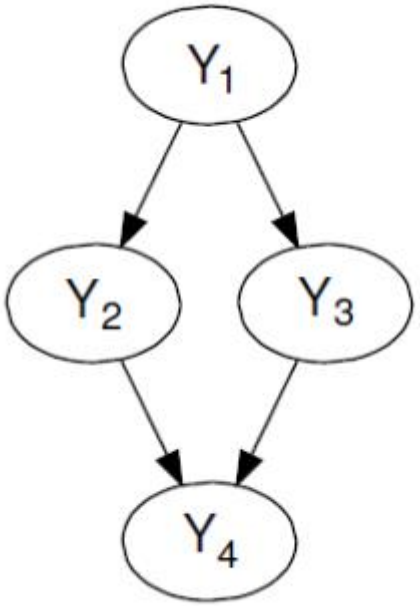
1. Additive Bayesian networks
2. Example Data set I
3. Procedure Data set II

Additive Bayesian networks: introduction

Y_1, …, Y_4 are random variables, presented as nodes.

Y_1 is a parent of the children Y_2 and Y_3.

Y_2 and Y_3 are parents of the child Y_4.



DAG: directed acyclic graph

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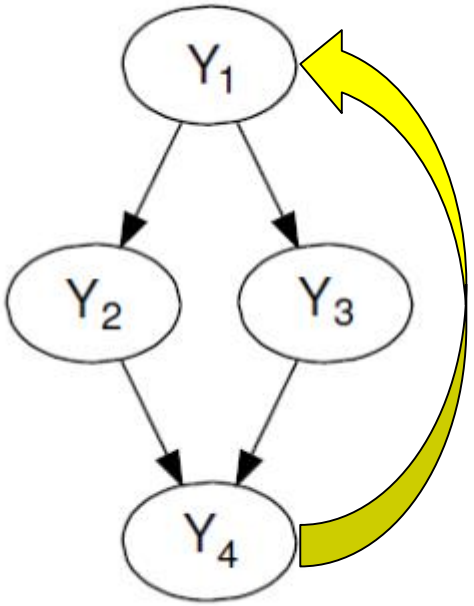

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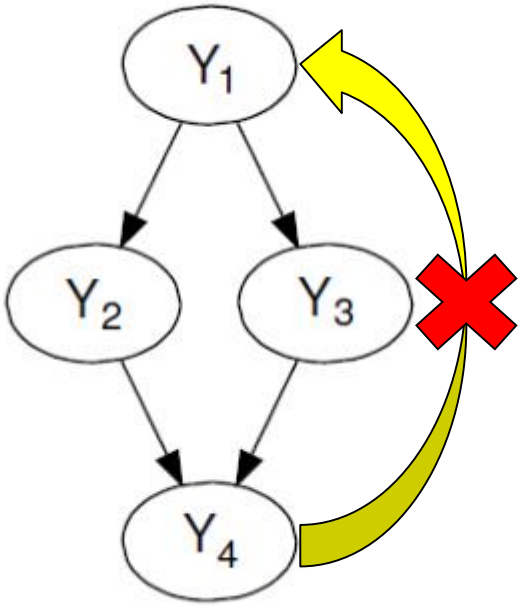

DAG: directed acyclic graph

Bayesian networks (BN)

BN represent the joint probability distributions of random variables.

A BN is a pair $N = (G, \Theta_G)$ with

- G, the structure of N, a directed acyclic graph (DAG) with variables Y_i as nodes and the conditional and marginal dependencies as arcs

- Θ_G the parametrisation of N, a set of model parameters , which determine the conditional probabilities $P(Y_i \mid parent(Y_i))$ for each node depending on the parents

A simple Bayesian network

www.toutpourlamaison.fr

brunch.co.kr

A simple Bayesian network

Rain influences whether the sprinkler is activated, and both rain and the sprinkler influence whether the grass is wet.

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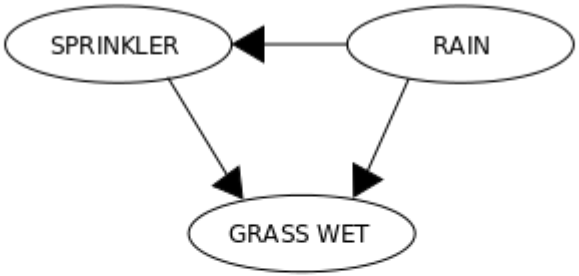

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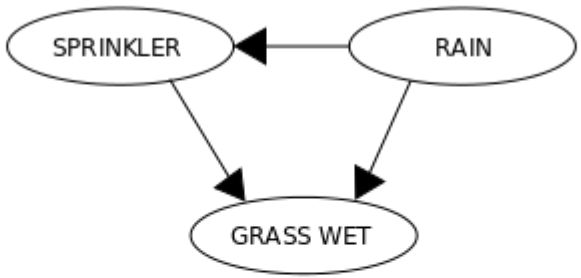
A simple Bayesian network

Rain influences whether the sprinkler is activated, and both rain and the sprinkler influence whether the grass is wet.

RAIN	SPRINKLER T	SPRINKLER F
F	0.4	0.6
T	0.01	0.99



RAIN T	RAIN F
0.2	0.8

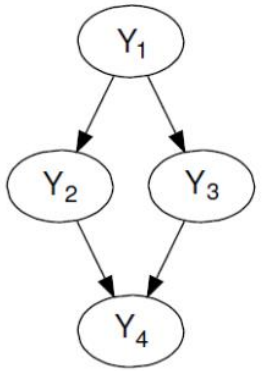
SPRINKLER	RAIN	GRASS WET T	GRASS WET F
F	F	0.0	1.0
F	T	0.8	0.2
T	F	0.9	0.1
T	T	0.99	0.01

https://en.wikipedia.org/wiki/Bayesian_network

Additive Bayesian networks

If $Y_1, \ldots, Y_4$ are binary random variables, and θ_i for $i = 1, \ldots, 4$ is the probability of observing a «success» and $P(Y_i = 1) = 1 - P(Y_i = 0)$,

the following parametrisation will constitute an abn:

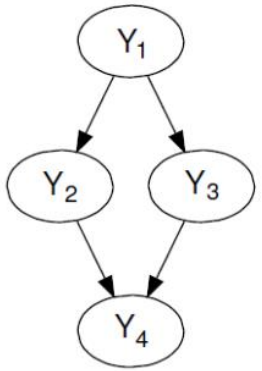


- Y_1 is independent: $\log\left(\frac{\theta_{Y_1}}{1-\theta_{Y_1}}\right) = \beta_{Y_{1,0}}$
- Y_2 is conditional dependent on Y_1: $\log\left(\frac{\theta_{Y_2}}{1-\theta_{Y_2}}\right) = \beta_{Y_{2,0}} + \beta_{Y_{2,1}} Y_1$
- Y_3 is conditional dependent on Y_1: $\log\left(\frac{\theta_{Y_3}}{1-\theta_{Y_3}}\right) = \beta_{Y_{3,0}} + \beta_{Y_{3,1}} Y_1$
- Y_4 is conditional dependent on Y_2 and Y_3: $\log\left(\frac{\theta_{Y_4}}{1-\theta_{Y_4}}\right) = \beta_{Y_{4,0}} + \beta_{Y_{4,2}} Y_2 + \beta_{Y_{4,3}} Y_3$

Additive Bayesian networks

Chain rule for the joint probability distribution

$$P(Y_1, Y_2, Y_3, Y_4) = P(Y_1)P(Y_2|Y_1)P(Y_3|Y_1)P(Y_4|Y_2, Y_3)$$



Example data I: Euthanasia in small animal practice

BMC Veterinary Research

Attitudes of Austrian veterinarians towards euthanasia in small animal practice: impacts of age and gender on views on euthanasia

Sonja Hartnack[1*], Svenja Springer[2], Marta Pittavino[3] and Herwig Grimm[2]

Hartnack *et al. BMC Veterinary Research* (2016) 12:26
DOI 10.1186/s12917-016-0649-0

University of Zurich[UZH]

messerli Forschungsinstitut
Vienna

Example data I: Euthanasia in small animal practice

εὐθανασία

eu~: good, well, right

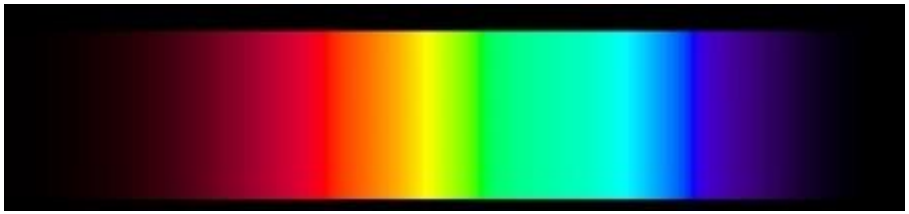
thánatos: death

“Vernünftiger Grund”
it is prohibited to kill an animal without a “good” reason.

Euthanasia

«the best and the worst of the profession»

- Changes in the human-animal relationship
- Ethical conflicts



Convenience Euthanasia — Anthropomorphism

«moral stress» Rollin (2009)

Questionnaire scenarios

An animal owner comes to your office with a young dog. This dog is severely ill, but therapy is possible. This therapy would be time-consuming, but there are chances of success. The owner rejects the therapy because he has neither enough time nor enough money. He wants you to euthanize the dog.

A dog owner comes to your office and wants you to euthanize her dog. She argues that the 15 year old dog does not fit to her living conditions anymore because she will travel with her family for some time and does not want to bring a dog at this age to the animal shelter.

Statements (n=26)

- It is easier for me to deal with euthanasia if I know that the animal would only have lived on for a short time.

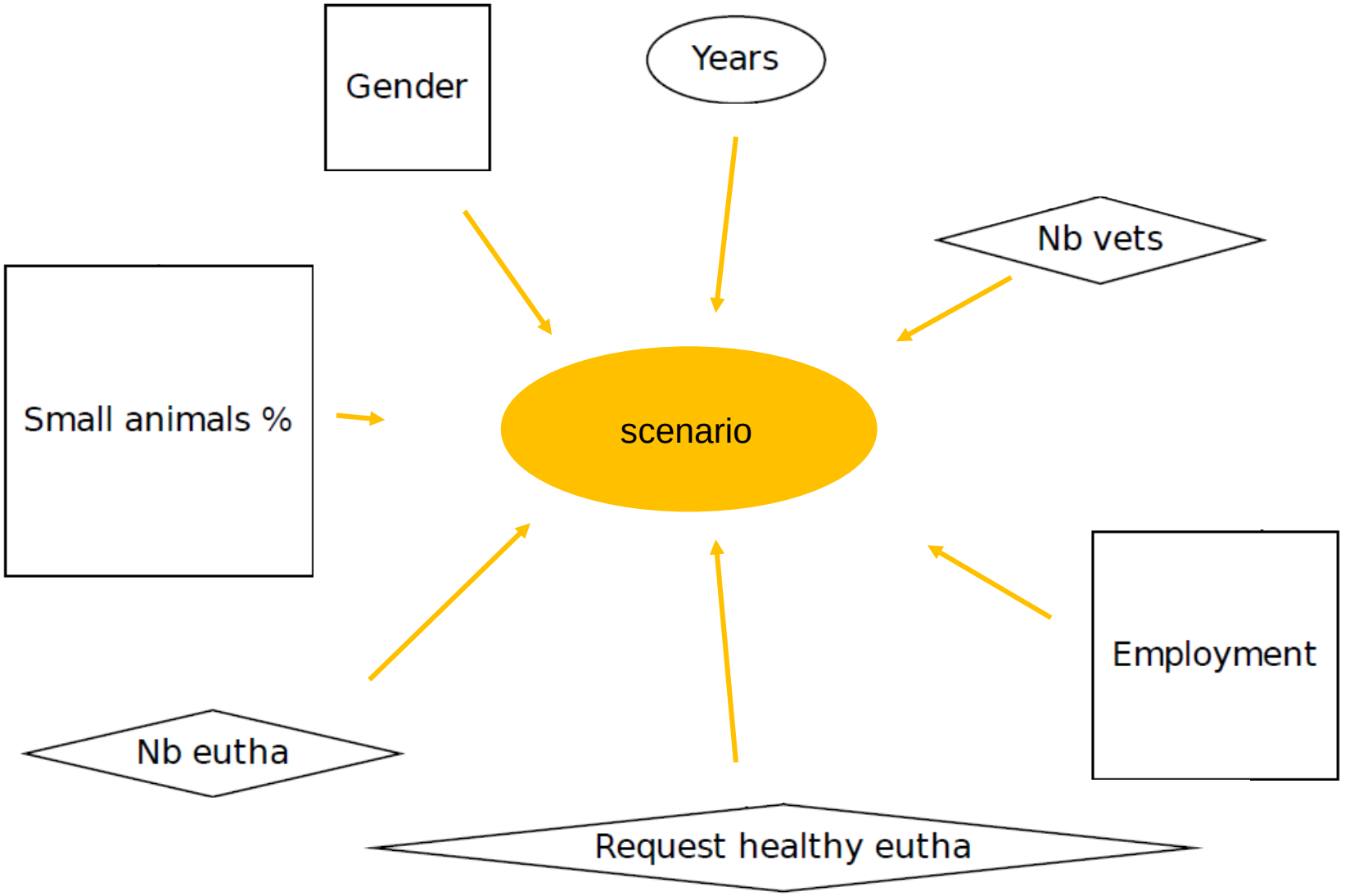
- Although I would reject euthanasia, I euthanize the animal because I am afraid that the owner will see another vet.

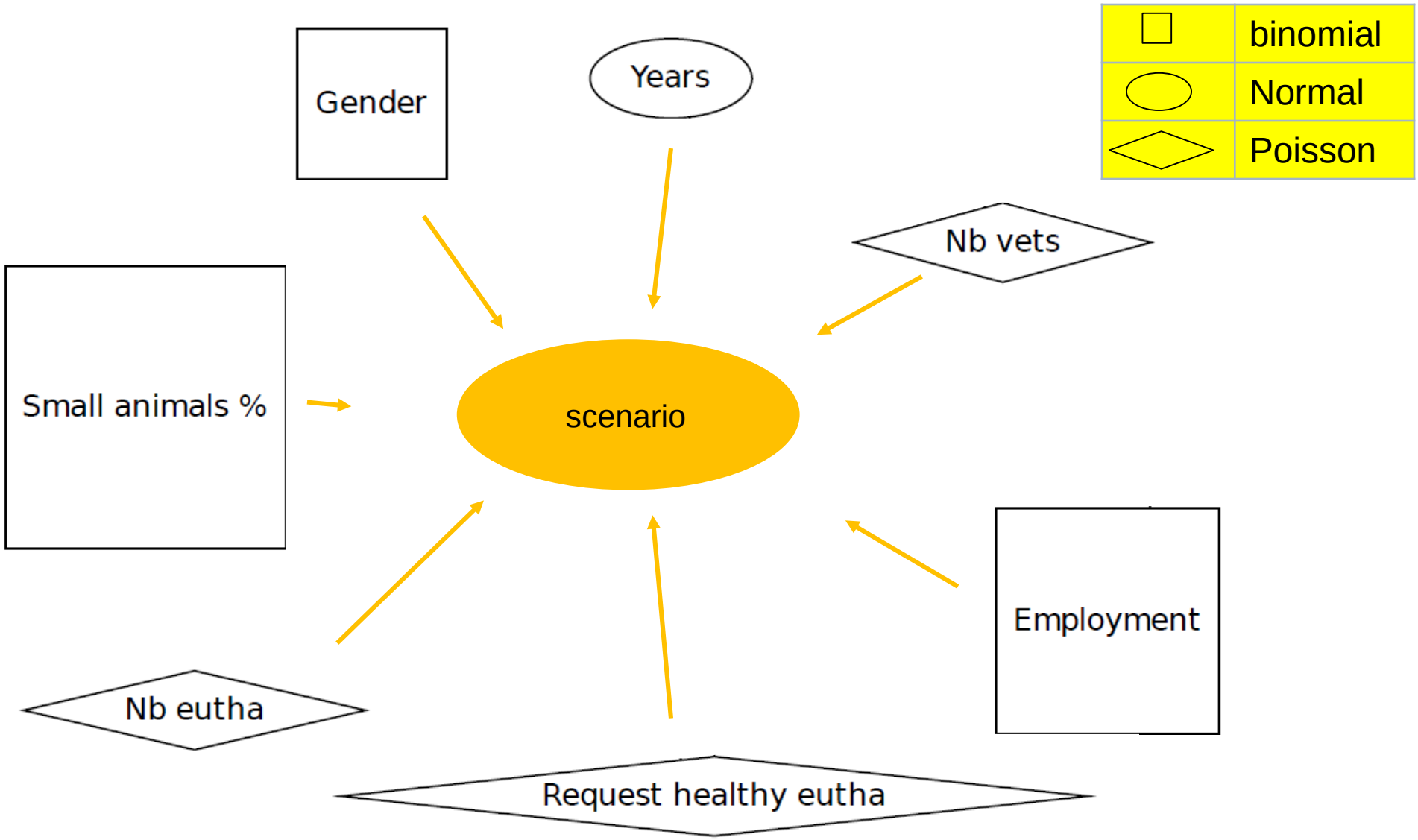
- It is easier for me to deal with euthanasia if the procedure is carried out according to the best technical standards.

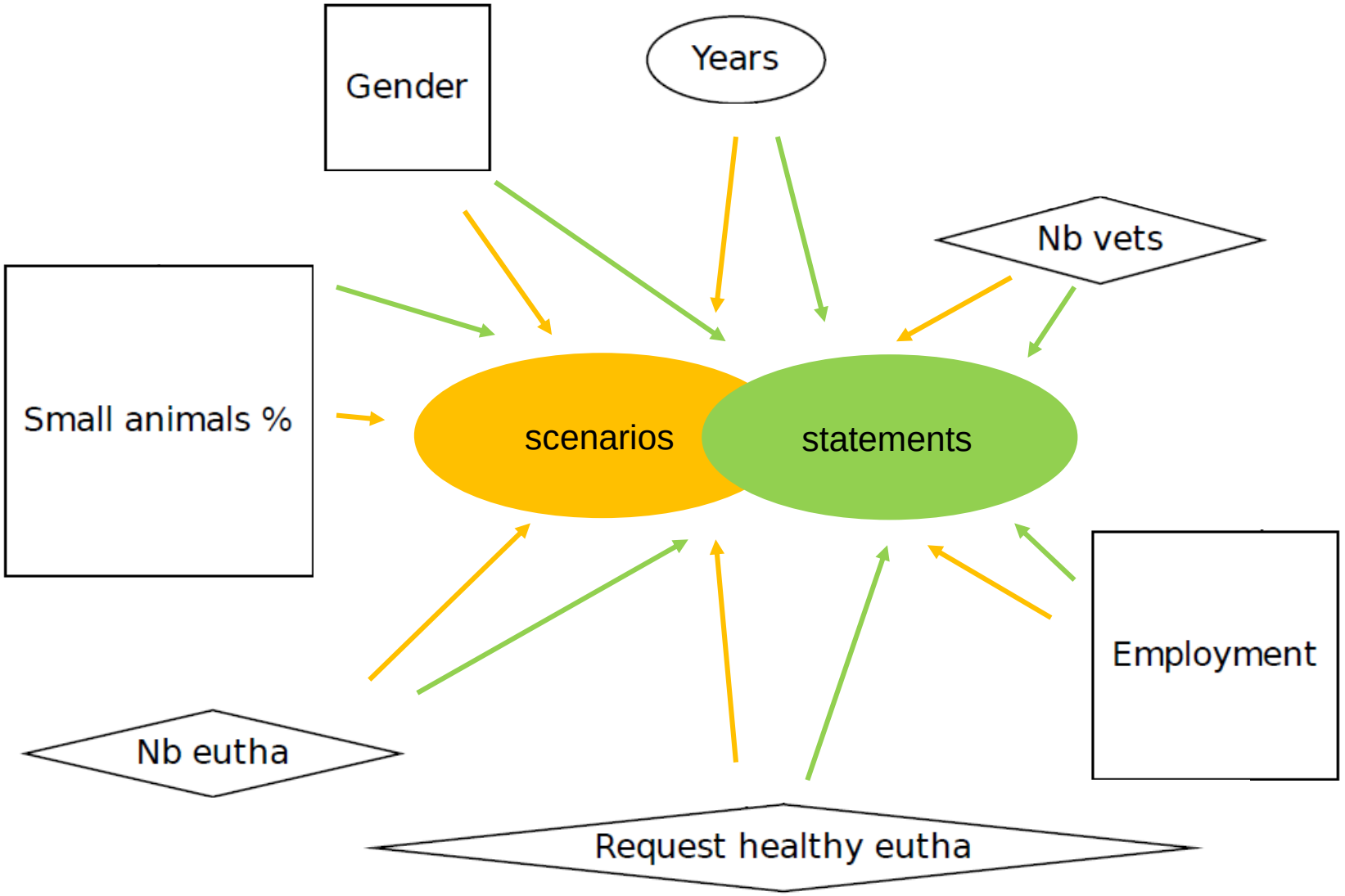
- …

Aims

- agreement with scenarios and statements?
- agreement influenced by demographic factors?
- analysis: regression and additive bayesian network models


Gender
Years
Nb vets
Small animals %
scenario
Employment
Nb eutha
Request healthy eutha


binomial
Normal
Poisson
Gender
Years
Nb vets
Small animals %
scenario
Employment
Nb eutha
Request healthy eutha


Gender
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scenarios
statements
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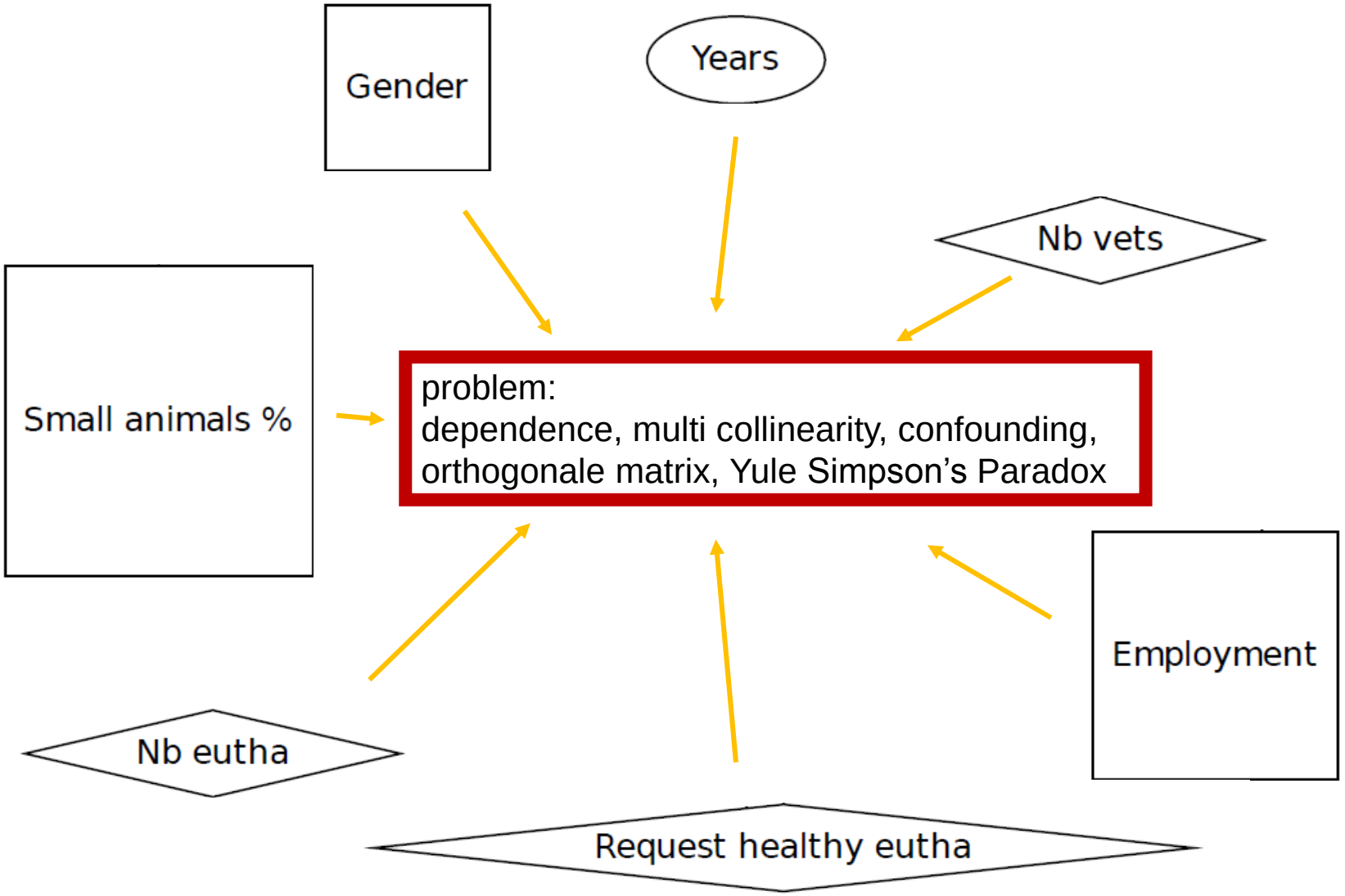
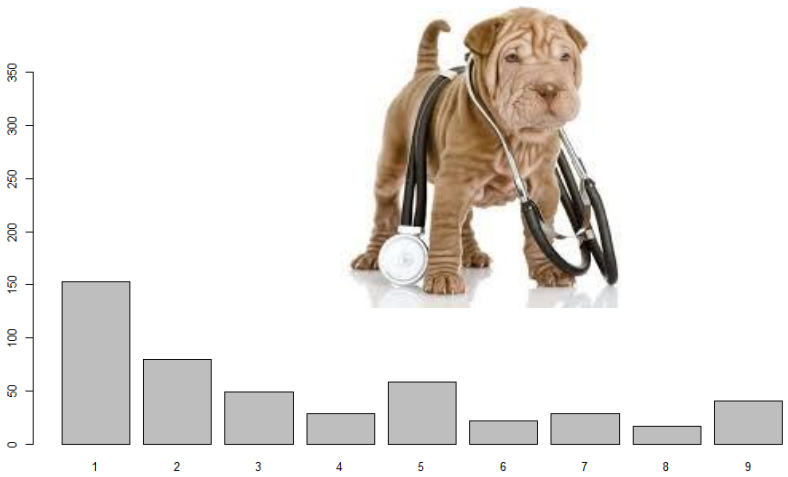
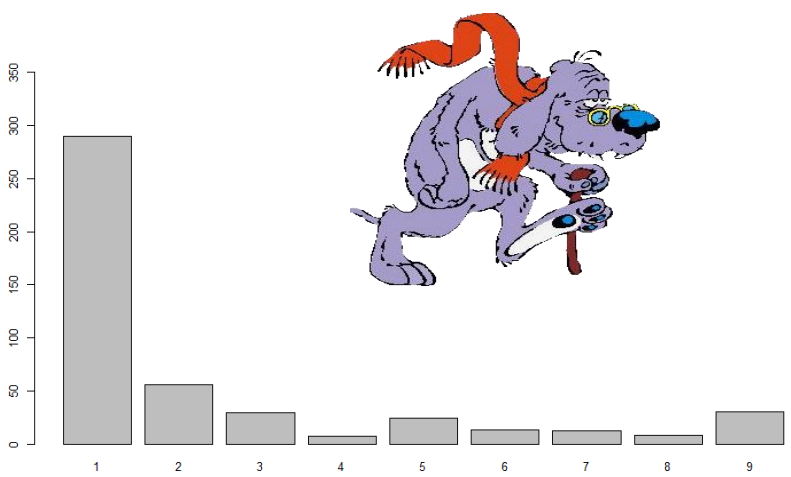
Request healthy eutha

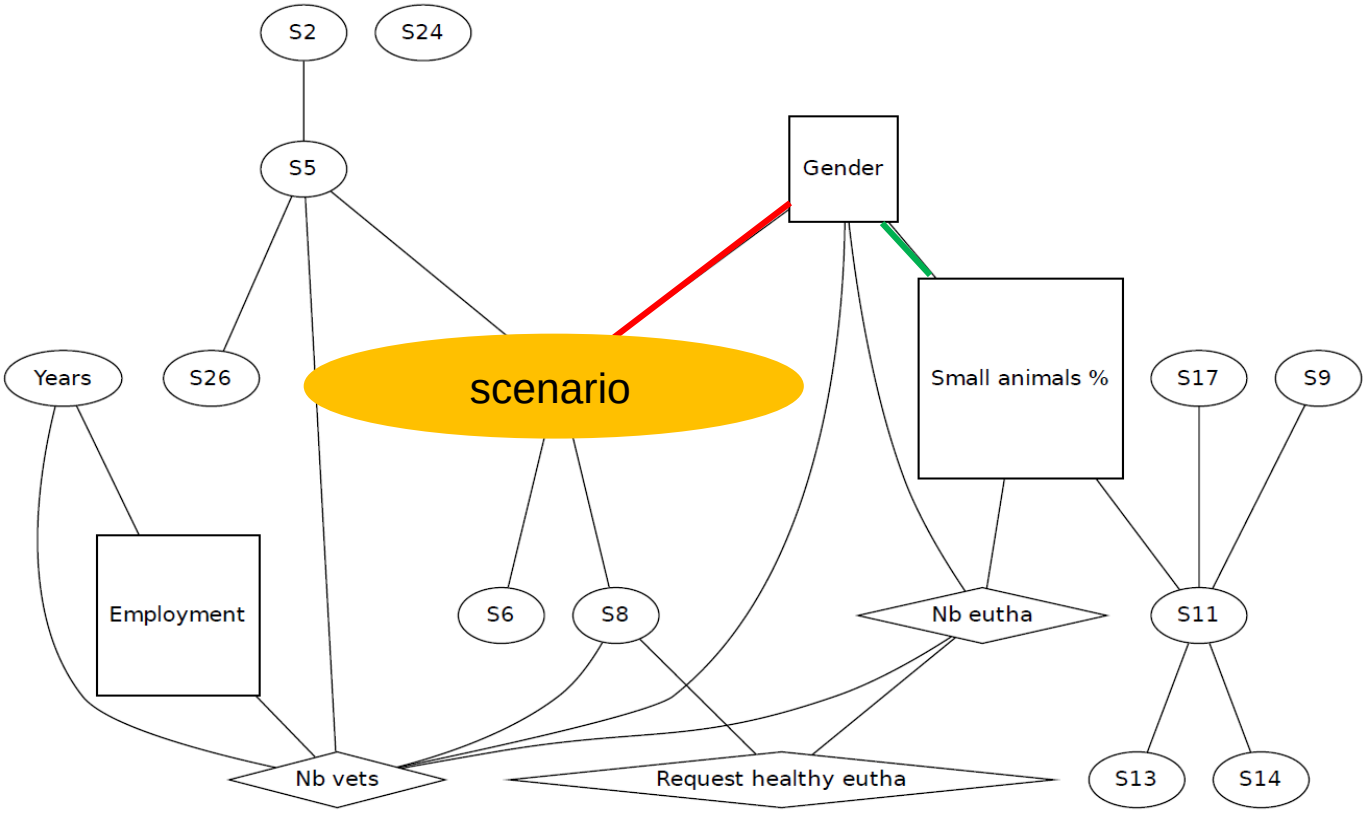

Gender
Years
Nb vets
Small animals %
problem:
dependence, multi collinearity, confounding,
orthogonale matrix, Yule Simpson's Paradox
Employment
Nb eutha
Request healthy eutha



agreement

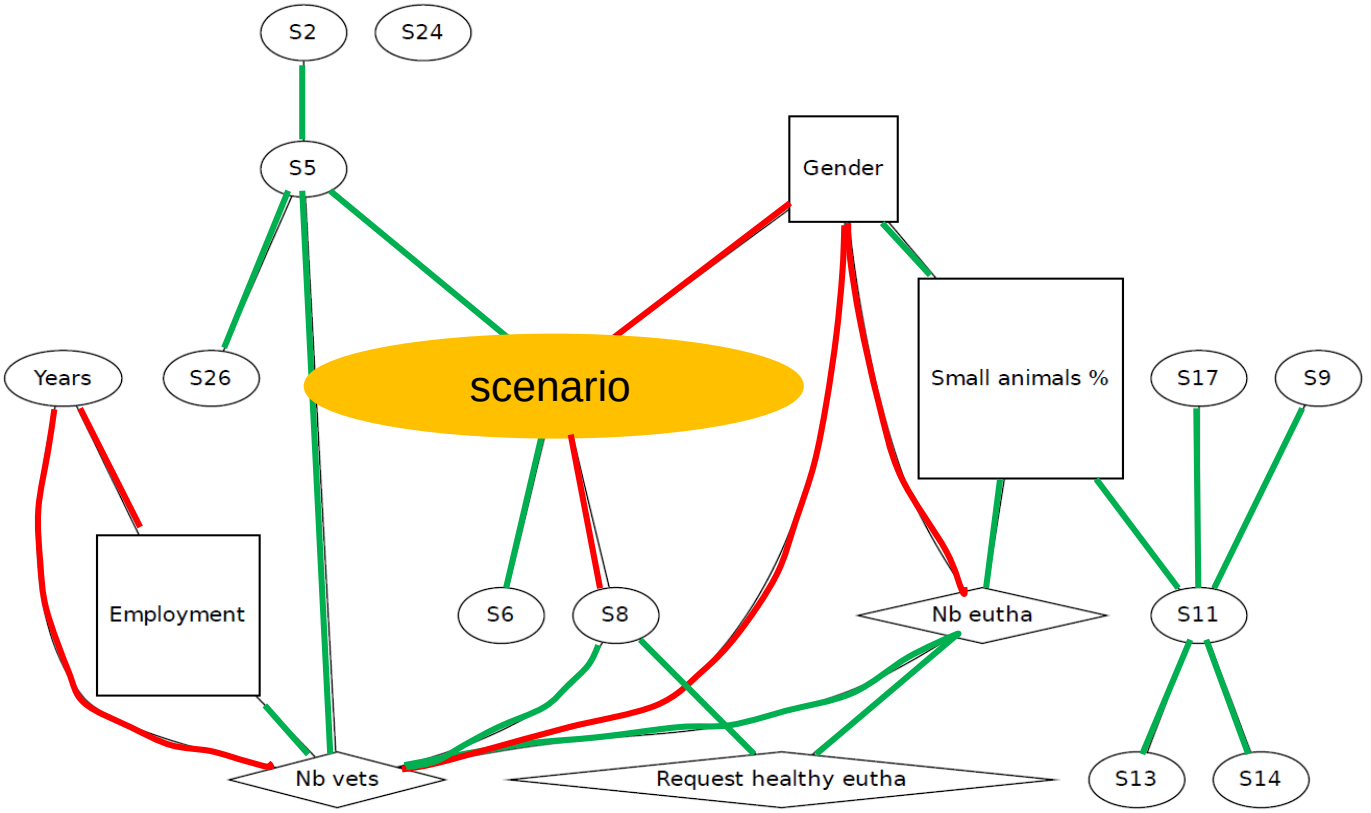


agreement



Small animal % ↓ [-1.6;-0.39]

M / F ↓ [-2.1;-0.95]



Small animal % ↓ [-1.6;-0.39]

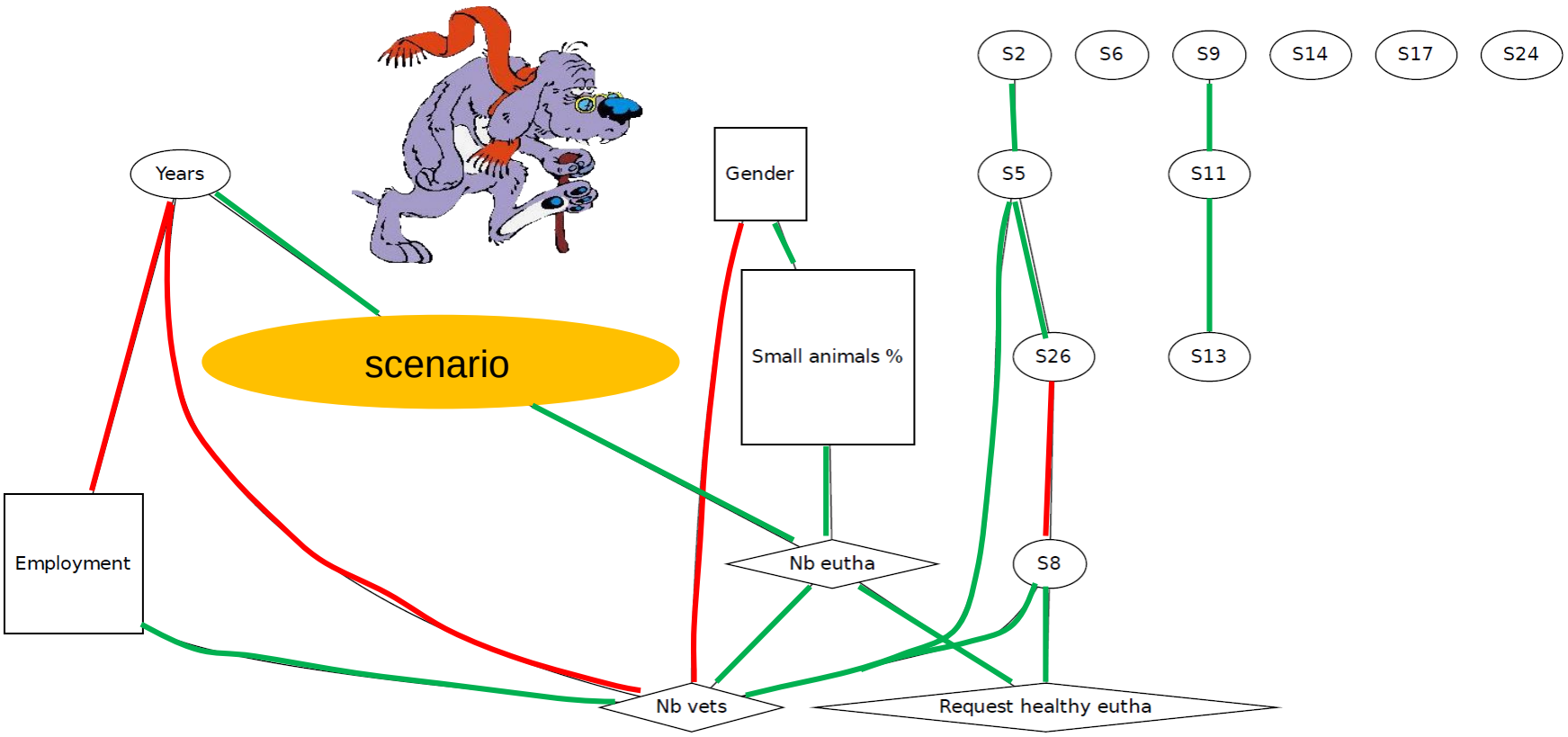
M / F ↓ [-2.1;-0.95]

scenario

S5:
Knowing that all veterinary medical, social and economic options have been considered makes it easier for me to deal with euthanasia.

S6:
It is easier for me to euthanize an animal if I see that the owner does not have a close relationship to his animal.

S8:
I am still not used to euthanizing animals.



Years	↓	[0.05;0.1]
Small animals %	↓	[-1.29;-0.14]
Nb eutha	↑	[0.09;0.25]
Request healthy eutha?	↓	[-0.12;0]

Break?

Procedure data set II: antimicrobial resistance

- Best fitting model (DAG)

- Adjust overfitting

http://www.r-bayesian-networks.org/

Procedure data set II: antimicrobial resistance

Identifying phenotypic associations in Salmonella antibiotic resistance patterns

Sonja Hartnack, Taurai Tasara, Herbert Hächler und Roger Stephan

Institute for Food Safety and Hygiene

Data set II: antimicrobial resistance

- National reference laboratory for enteropathogenic bacteria (NENT)
- 399 human Salmonella isolates (2004-2009)
- Serovar Kentucky (131), Virchow (188) und Hadar (81)

Data set II: antimicrobial resistance

- Agar disk diffusion test (in mm) for 13 antibiotics
- Information «resistant», «susceptible» (intermediate) CLSI

- Nalidixic acid (66%), Tetracycline (46%), Sulfamethoxazole (37%), Ampicillin (29%), Trimethoprim (27%), Streptomycin (27%), Cefalotin (20%), Ciprofloxacin (19%), Gentamicin (10%), Chloramphenicol (10%), Kanamycin (7%), Amoxicillin-clavulanic acid (1%), Cefotaxim (0%)

- 78 different resistance patterns, frequencies (1-90)

Multiple antimicrobial resistance

Presence of resistance patterns

- Similar chemical structure
- Similar action
- Genetically related
- Simultaneously applied
- ….

First step to describe associations between different resistance patterns which are systematic.

Procedure data set II: antimicrobial resistance

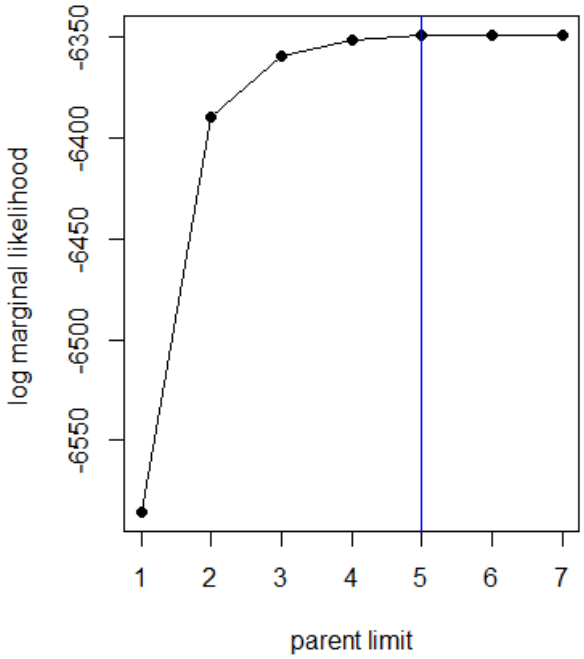
Best fitting model (DAG)

- exact structure discovery approach (Koivisto & Sood, 2004)
- uniform structural prior, uninformative priors
- increase number of parents per node (1-9)
- goodness of fit metric: marginal likelihood (MacKay 1992)

- Preparing data
  - Binary coding of three serovars
  - Considered inhibition zones as normally distributed

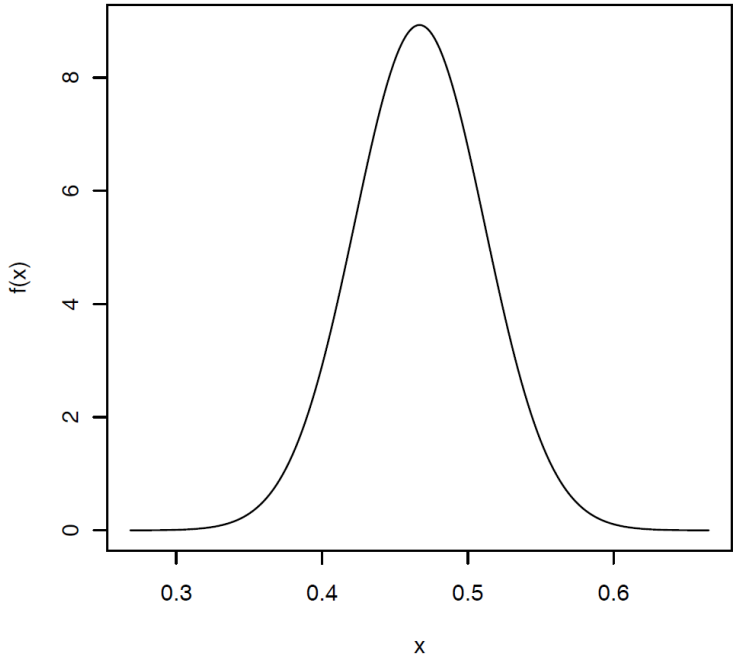
Best fitting model (DAG)

Compare goodness-of-fit for different parent limits

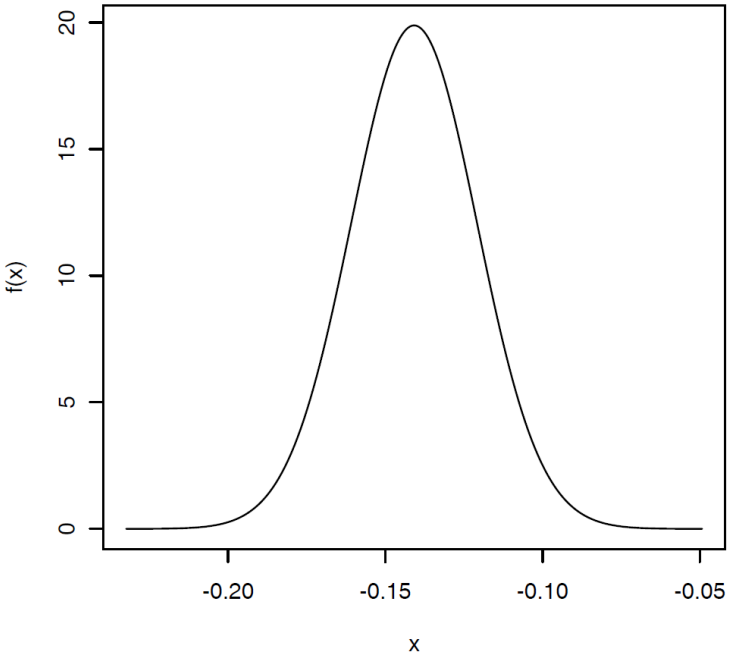


Best fitting model (DAG)

Posterior marginal densities



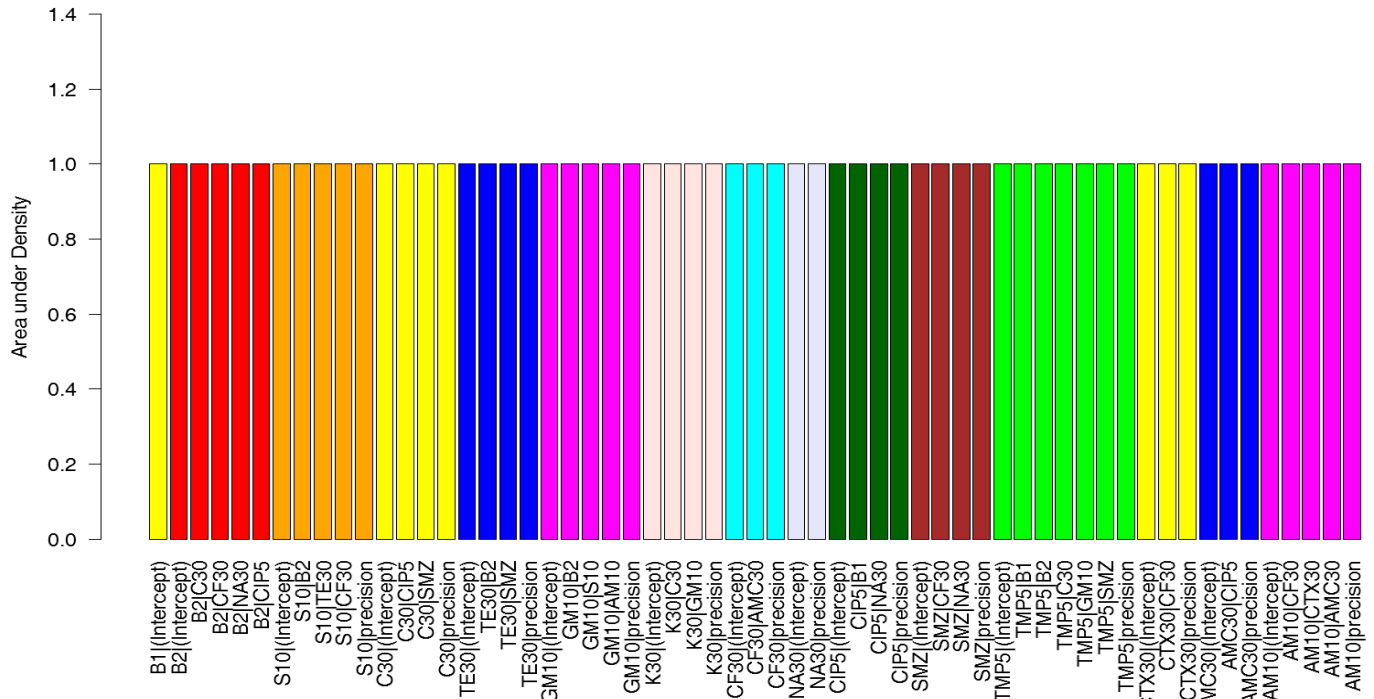
Streptomycin and Gentamicin



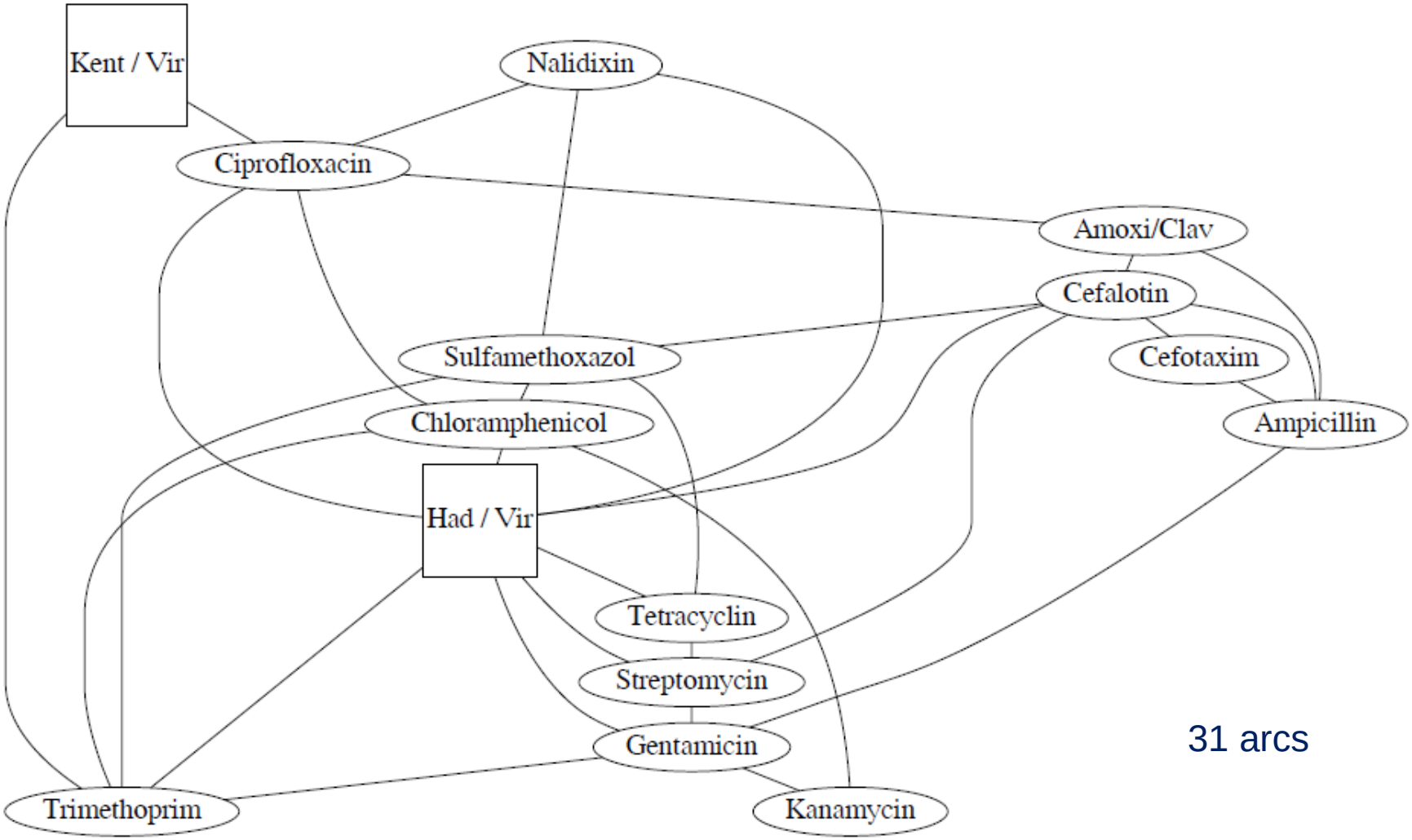
Cefotaxim und Ampicillin

Best fitting model (DAG)

Approximative area under densities



Best fitting model (DAG)



31 arcs

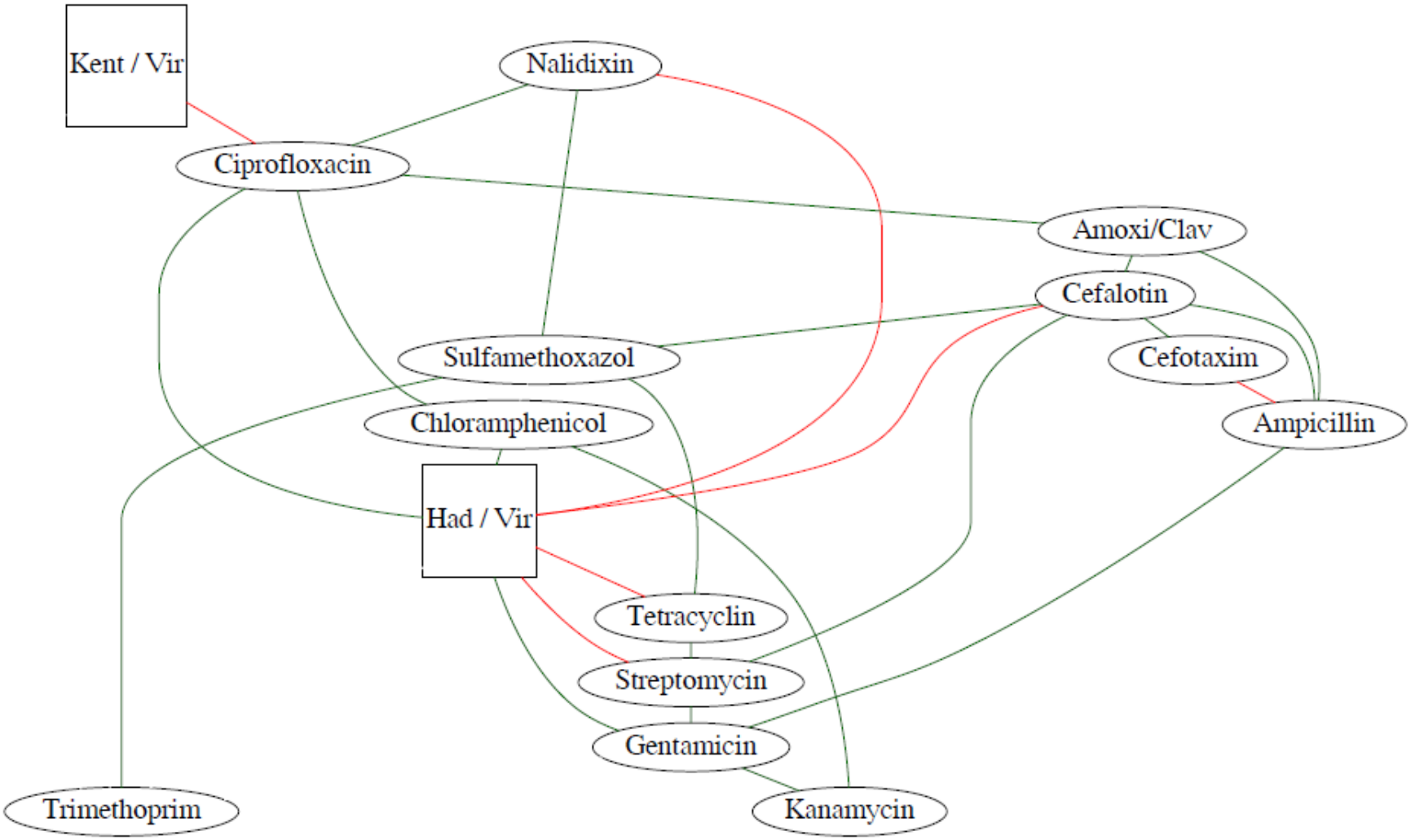
Procedure data set II: antimicrobial resistance

Adjust overfitting

- Standard parametric bootstrapping (Friedman 1999)
- MCMC in JAGS (Plummer 2003), 10’000 bootstraps
- Threshold 50% for retaining arcs

ABN
http://r-bayesian-networks.org/

Best DAG: posterior marginal quantiles



Thank you!